A Theory of Dynamic Product Awareness and Targeted Advertising*

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* The views expressed in this presentation are the authors' and may not represent those of Banco de España or the Eurosystem.

Motivation

- Firms have long used **advertising** to spread product awareness.
  - Traditional methods: radio and TV ads, billboards, door-to-door sales, ...
  - Targeted methods: mailing lists, customer catalogs, online ads, ...

- Advances in technology (social networks, search engines, big data, ...) have increased efficiency of ADV.
  - Share of digital in total ADV spending $\rightarrow$ From **4%** in 2000 to **57%** in 2020 (**70%** expected in 2023).

- Do these changes have an effect on how customers are reached and how markets are structured?

This paper:

New information-based theory of product lifecycles to understand ...

(i) ... how expanding consumer choice sets affect market and macro dynamics;

(ii) ... how better ADV technologies affect competition, sorting, markups, misallocation, welfare.

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Outline

1. Theory: A GE Model of Dynamic Product Awareness

- Key features:
  1. *Heterogeneous consumers* → (i) idiosyncratic tastes (*exogenous*); (ii) incomplete awareness sets (*endogenous*).
  2. *Homogeneous firms* → Take advantage of limited awareness and exploit customers through markups.
- Two advertising technologies:
  1. *Traditional* → Increase consumer contact rate ⇒ Consumers find preferred product faster (↑ **consumer sorting**).
  2. *Targeted* → Find high-valuation consumers with higher likelihood (↑ **match quality** but also ↑ **segmentation**).

2. Application: The Rise of Targeted Advertising (United States, 2005-2014)

- Two calibrations → Match the increase in share of digital ADV (↑ targeting) in the period 2005-2014.
- In the 2014 calibration → Both forms of ADV more cost-effective, but targeting now relatively cheaper.
  - ... **match quality** ↑ → Higher-quality matches formed with fewer connections (customer misallocation ↓).
  - ... **consumer sorting** ↓ → Awareness expands more slowly, more segmentation ⇒ market power ↑
- **Counterfactual:** Had ADV technology not improved, welfare would have been higher despite worse sorting.

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Related Literature

- **Customer Capital in Trade and Macro:**

  Fishman and Rob (2003), Bergemann and Välimäki (2006), Luttmer (2006), Arkolakis (2010, 2016), Dinlersoz and Yorukoglu (2012), Drozd and Nosal (2012), Gourio and Rudanko (2014), Fitzgerald, Haller and Yedid-Levi (2017), Paciello, Pozzi and Trachter (2019), Afrouzi, Drenik and Kim (2020), Roldan-Blanco and Gilbukh (2021), Ignaszak and Sedláček (2021), Einav, Klenow, Levin and Murciano-Goroff (2022).

  Contribution: New information-based interpretation.

- **Intangibles and Market Power:**

  Aghion, Bergeaud, Boppart, Klenow and Li (2019), Cavenaile, Celik, Tian (2022), Weiss (2022), De Ridder (2022).

  Contribution: New mechanism operating through the extensive-margin of demand.

- **Advertising in Economics:**

  Dorfman and Steiner (1954), Butters (1977), Becker and Murphy (1993), Bagwell (2007), Goeree (2008), Dinlersoz and Yorukoglu (2012), Guthmann (2020), Greenwood, Ma and Yorukoglu (2021), Rachel (2021), Cavenaile and Roldan-Blanco (2021), Argente, Fitzgerald, Moreira and Priolo (2021), Klein and Şener (2022), Baslandze, Greenwood, Marto and Moreira (2022).

  Contribution: Focus on targeted vs non-targeted ADV, feature new GE effects.

Model Assumptions

Assumptions I: Demographics

- **Consumers:** Measure-one continuum, with preferences over a single final good.
- **Final good:** Assembled from a continuum mass $\boldsymbol{M_t} > 0$ (*endogenous*) of product categories.
  - Category $m \in [0, \boldsymbol{M_t}]$ is populated by a finite number $N \in \mathbb{Z}_+$ of identical firms $i \in \mathcal{I} \equiv \{1, 2, \ldots, N\}$.
  - A "product" is uniquely indexed by $(i, m) \in \mathcal{I} \times [0, \boldsymbol{M_t}]$.
- **Product market dynamics:**
  - Each instant $t \in \mathbb{R}_+$, an "innovator" invests resources to find a blueprint for a new product category.
  - All N firms enter together upon product creation, and all exit together at rate $\delta_M > 0$ (*obsolescence*).
- **Consumer heterogeneity:**
  1. ... in preferences:
     - Permanent idiosyncratic preferences over (i, m) products, $\xi_{imj} \sim \text{Gumbel}(0, 1)$.
     - Distribution of preferences is independent across product categories, i.e. $\xi_{imj} \perp \xi_{im'j}, \forall m \neq m'$.
  2. ... in awareness:
     - Consumer j is aware of, and can only consume from, a subset of products from each category.

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Assumptions II: Preferences, Technology and Information

- **Preferences:** Consumer $j \in [0,1]$:

$$\max \int_0^{+\infty} e^{-\rho t} \frac{C_{jt}^{1-\gamma}}{1-\gamma} \, \mathrm{d}t, \qquad \text{with } C_{jt} = \left[\int_0^{M_t} \left(\sum_{i \in A_{mjt}} \overline{\Gamma} e^{\sigma \xi_{imj}} c_{imjt} \right)^{\frac{\kappa-1}{\kappa}} \mathrm{d}m \right]^{\frac{\kappa}{\kappa-1}}$$

  where

  - $c_{imjt} > 0$ is the quantity purchased of product (i, m).
  - $A_{mjt} \subseteq \mathcal{I} = \{1, \ldots, N\}$ is the consumer's awareness set, which evolves endogenously via ADV.

- **Technology:** Identical firms $i \in \{1, \ldots, N\}$, use a common Cobb-Douglas technology (w/ constant TFP):

$$y_{imt} = z \, k_{imt}^{\alpha} \, l_{imt}^{1-\alpha}, \qquad \text{with } z > 0, \alpha \in (0,1)$$

- **Information:**
  - Firm cannot observe A_{mjt} and ξ_{imj} for any consumer $j \in [0,1]$.
  - *But*... they have complete information on:
    1. Joint distribution over (A_{mjt}) sets that contain the firm and their corresponding (ξ_{imj}) shifters.
    2. Actions of other firms within the product category $\rightarrow$ Compete in prices (à la Bertrand).

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Assumptions III: Advertising

1 **Traditional advertising:**

- Choose contact rate of new customers, $\theta > 0$, constant over time and across firms.
- Determines evolution of awareness sets ("urn-ball" without replacement). ▸ Awareness Law of Motion

2 **Targeted advertising:**

- Recall → Tastes for *population* of consumers are $\xi_{imj} \sim \text{Gumbel}(\ 0\ , 1)$.
- At age $a \geq 0$, tastes of consumers *who are aware* of firm i are $\sim \text{Gumbel}\Big(\ \ln\left(\mu_i(a)\right)\ , 1\Big)$.
  - Firms only choose $\mu_{0,i} \ \equiv\ \mu_i(0) \geq 1$, at age $a = 0$.
  - Law of motion for targeting:

$$\ln\left(\mu_i(a)\right) = \ln\left(\mu_{0,i}\right)\Big(1 - \underbrace{s_i(a)}_{\substack{\text{Network} \\ \text{saturation}}}\Big), \qquad \text{where } \underbrace{s_i(a) \equiv \sum_{A \ni i} \underbrace{\widehat{f}(a, A)}_{\substack{\text{Density of} \\ \text{awareness set } A}}}_{\substack{\text{Proportion of awareness sets} \\ \text{that contain the firm}}}$$

- ADV costs per firm (paid in units of final good) $\rightarrow$ $d(\theta, \mu_0) = \nu\theta^2 + \eta(\mu_0 - 1)^2$, with $\nu, \eta > 0$.

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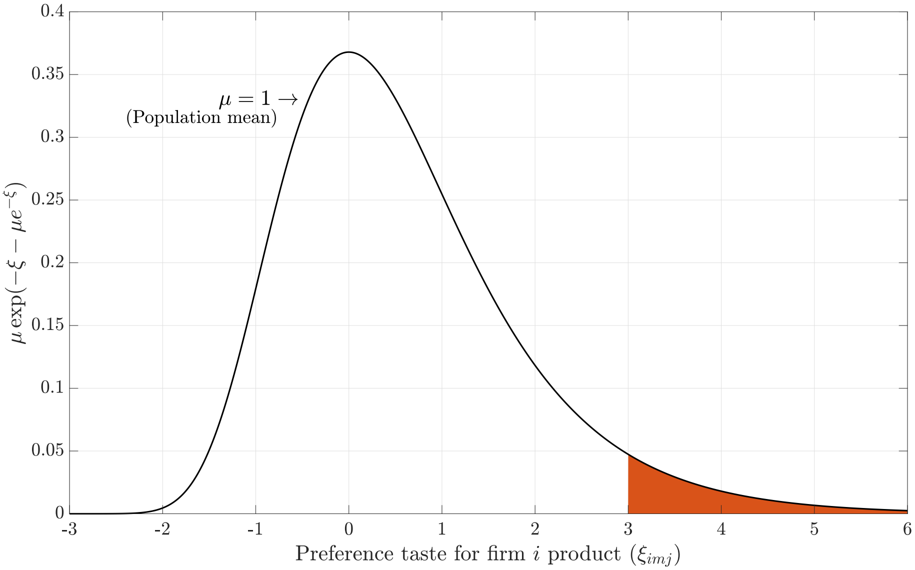
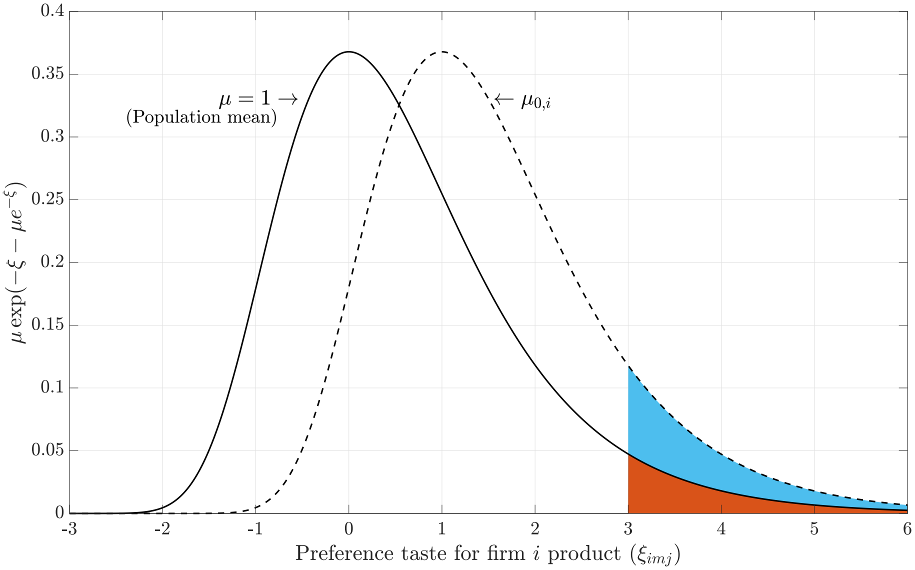
Assumptions IV: Visualizing Targeting

- ξ distribution for **population** of consumers has mean $0 = \ln(\mu)$, i.e. an "undistorted" Gumbel with $\mu = 1$.



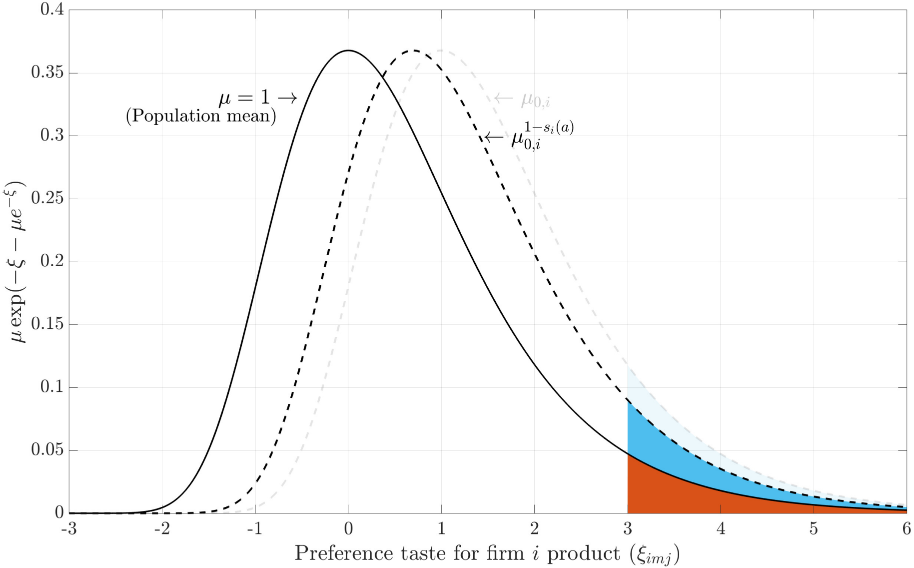
Assumptions IV: Visualizing Targeting

- At age $a = 0$, firm gets to draw from a distorted Gumbel with mean $\mu_{0,i} > 1$ (chosen once-and-for-all).



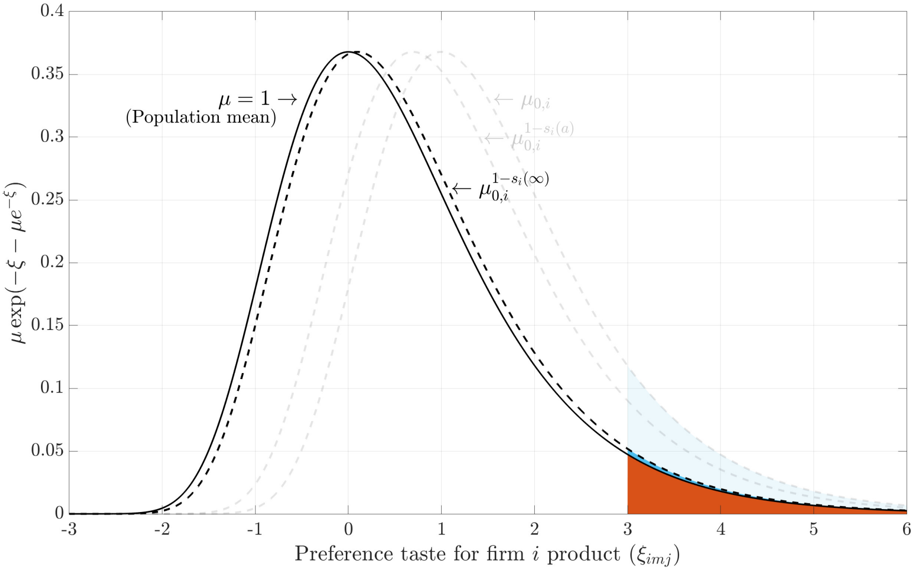
Assumptions IV: Visualizing Targeting

- As product category ages ($a \uparrow$), firm's network saturates ($s(a) \uparrow$) $\rightarrow$ Becomes "harder to distort" ($\mu_i(a) \downarrow$).



Assumptions IV: Visualizing Targeting

- As $a \to +\infty$, every firm is in every awareness set: $f_N(a) \to 1$ and $s(a) \to 1$, so $\mu_i(a) \to 1$.



Equilibrium

Equilibrium I: Consumer Problem

Given real income Ω_{jt}, price index P_{jt}, and nominal prices $(\widehat{p}_{imt})$ for $i \in A_{mjt}$:

1. **Extensive-margin:** Consumer j purchases from firm i and from no other firm $i' \in A_{mjt} \backslash \{i\}$ iff

$$\ln\left(\frac{\widehat{p}_{i'mt}}{\widehat{p}_{imt}}\right) > \sigma\left(\xi_{i'mj} - \xi_{imj}\right).$$

2. **Intensive-margin:** If consumer j chooses firm $i \in A_{mjt}$, her demand is:

$$y^d_{imjt} = \overline{\Gamma}^{\kappa-1} e^{\sigma(\kappa-1)\xi_{imj}} \left(\frac{\widehat{p}_{imt}}{P_{jt}}\right)^{-\kappa} \Omega_{jt},$$

- In eq'm, each consumer purchases from only one firm in each product category (almost surely).
- For this one firm, intensive demand is downward-sloping, $\left(\frac{\widehat{p}_{imt}}{P_{jt}}\right)^{-\kappa} \Omega_{jt}$.

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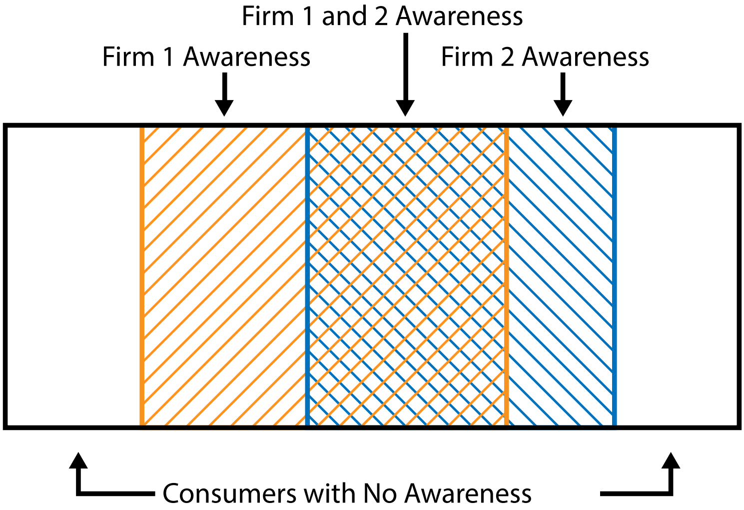

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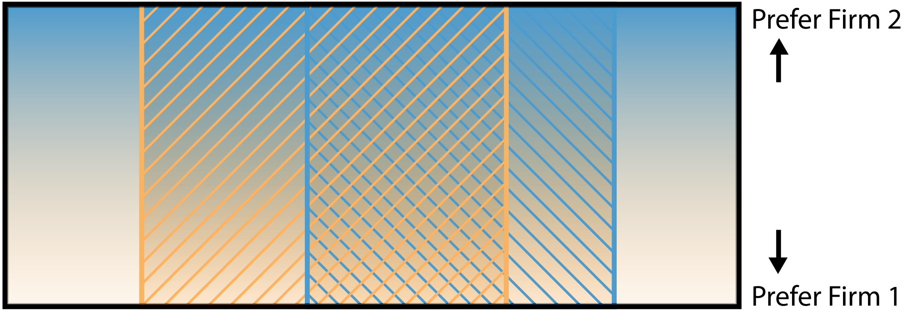

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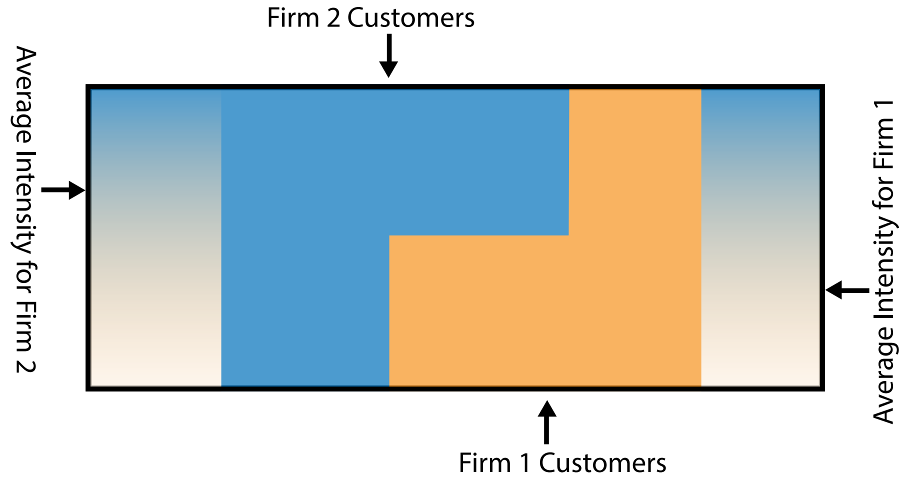

Equilibrium II: Firm Problem and Markups

- Focus on a *symmetric equilibrium* (in prices and targeting).
- **Targeting** is a demand shifter, **sorting** matters only through *size* of (non-empty) sets, $\widehat{n} \equiv |A|$. Details

Firm demand:
$$y_t(a) = \underbrace{(1 - f_0(a))}_{\text{Overall awareness}} \underbrace{\mu(a)^{\sigma(\kappa-1)}}_{\text{Targeting}} \underbrace{p(a)^{-\kappa} \frac{\Omega_t}{N}}_{\text{Downward-sloping demand}} \underbrace{q(a)}_{\text{Sorting}} \qquad \text{where } q(a) \equiv \mathbb{E}_a\left[\widehat{n}^{\sigma(\kappa-1)}\right]$$

Markups. If a symmetric pure-strategy Nash equilibrium exists for N firms, then:

$$\Lambda(a) \equiv \frac{p(a)}{mc_t} = \frac{\varepsilon(a)}{\varepsilon(a)-1}, \qquad \text{where} \quad \underbrace{\varepsilon(a)}_{\text{Total demand elasticity}} = \underbrace{\kappa}_{\text{Intensive-margin elasticity}} + \underbrace{\left(-\frac{\partial \ln(q(a))}{\partial \ln(p)}\right)}_{\text{Extensive-margin elasticity}}$$

- **Mechanism:**
  - When product is young ($a \approx 0$), awareness sets are sparse $\rightarrow$ EM price-elasticity low.
  - As $a \uparrow$, consumers sort into better options $\rightarrow$ EM elasticity increases $\rightarrow$ Competition intensifies $\rightarrow \Lambda(a) \downarrow$

Equilibrium II: Firm Problem and Markups

- Focus on a *symmetric equilibrium* (in prices and targeting).
- **Targeting** is a demand shifter, **sorting** matters only through *size* of (non-empty) sets, $\widehat{n} \equiv |A|$. ▸ Details

Firm demand:

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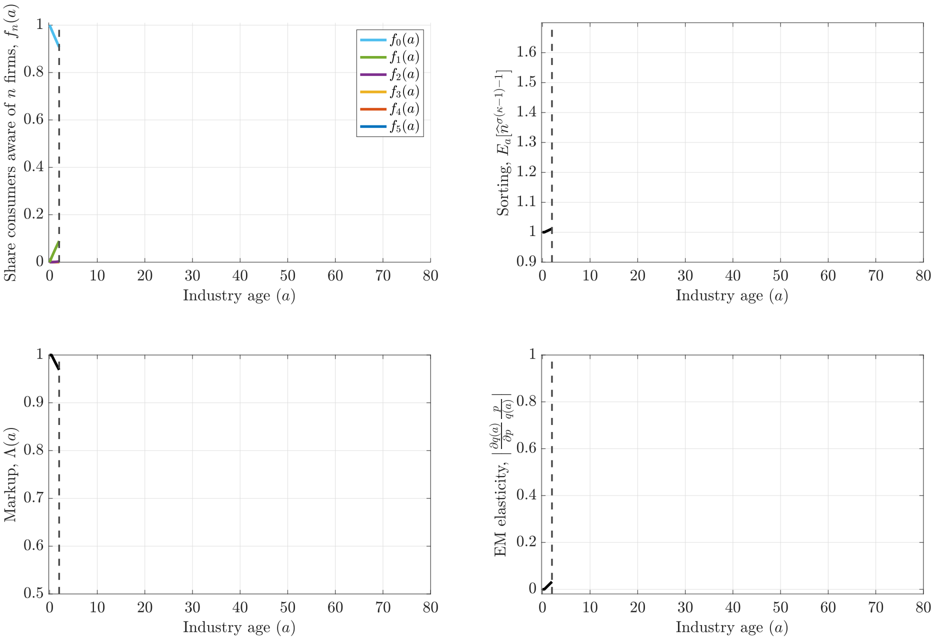
Equilibrium III: Illustrative Example



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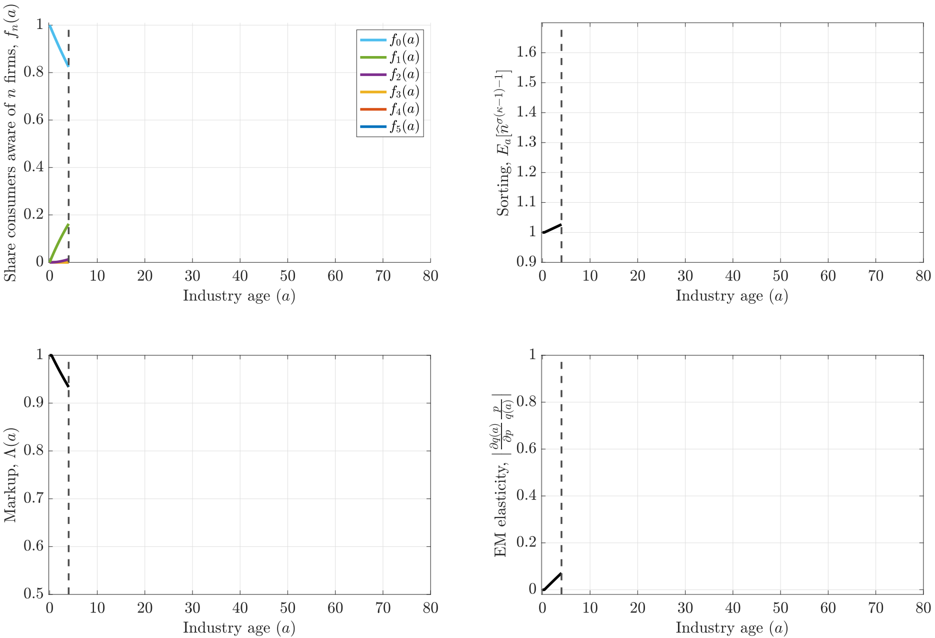

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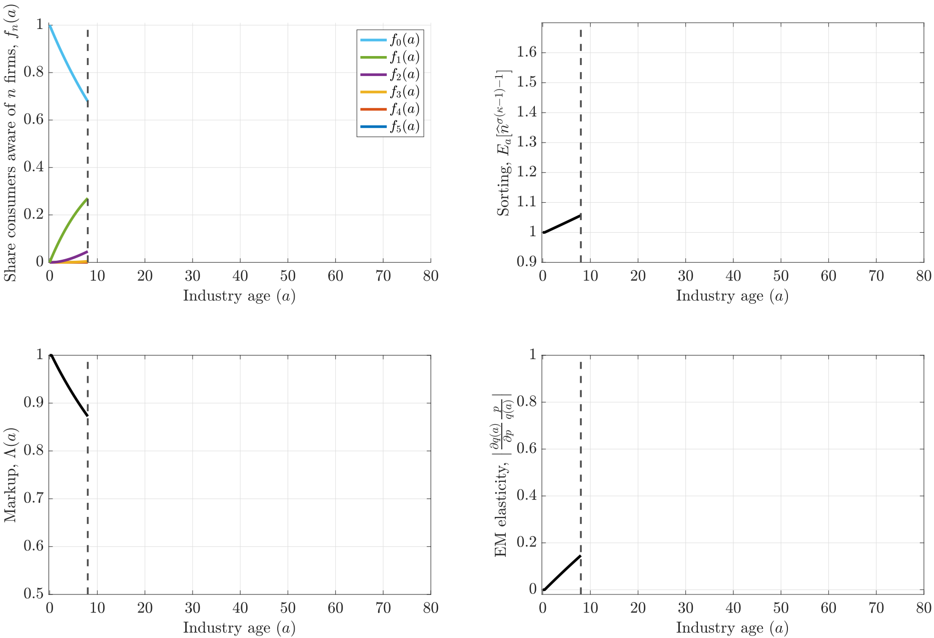

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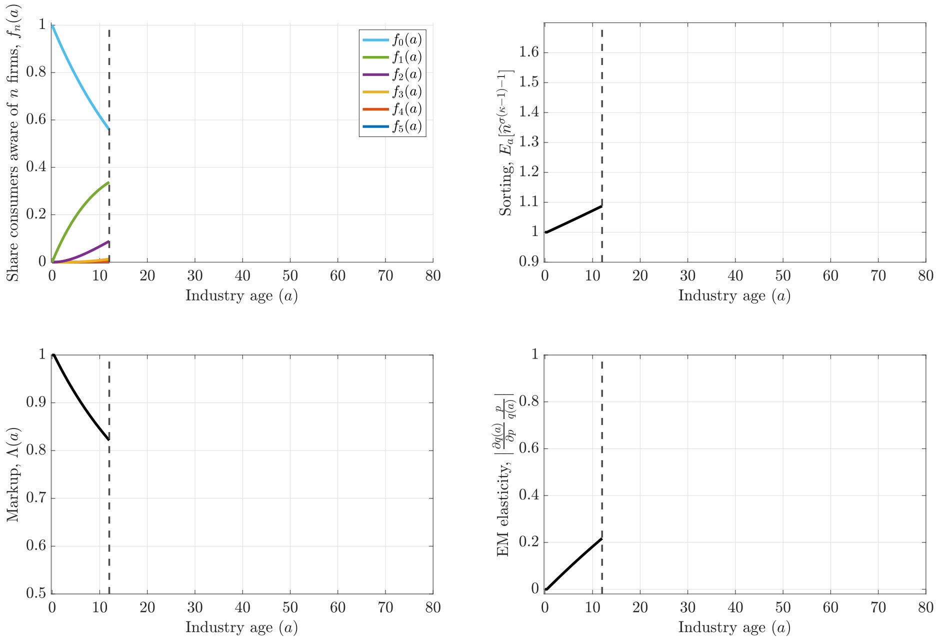

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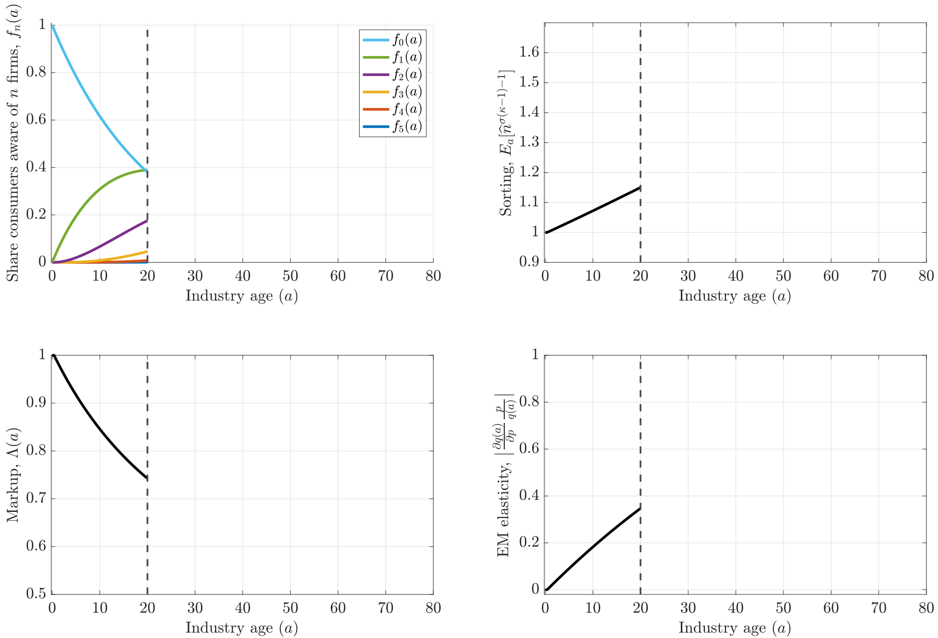

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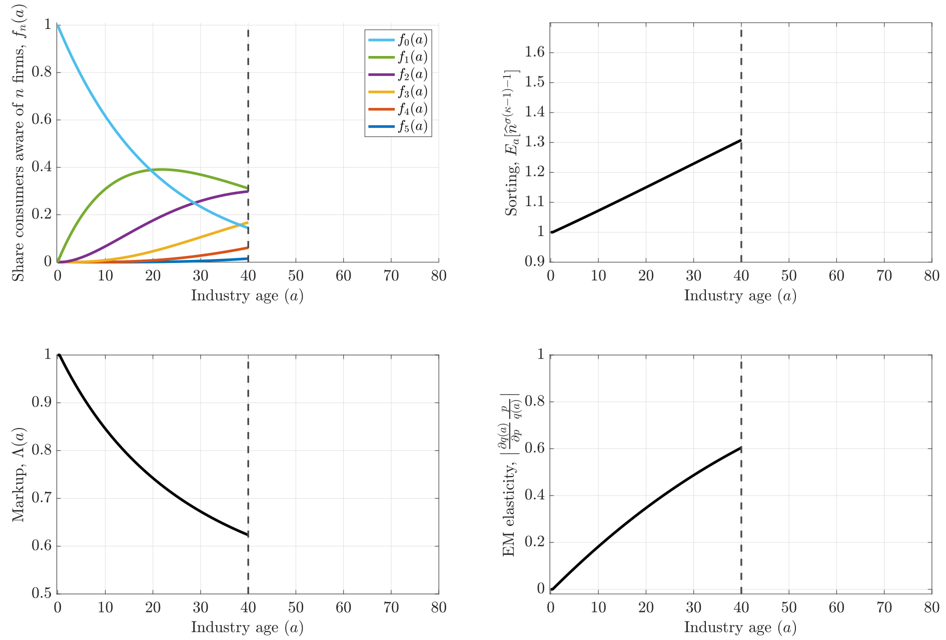

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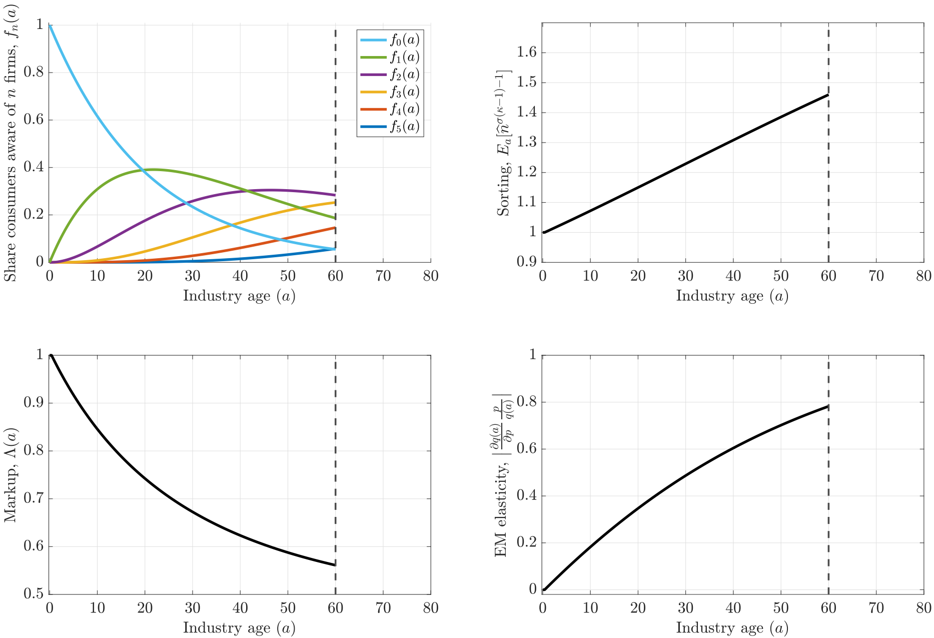

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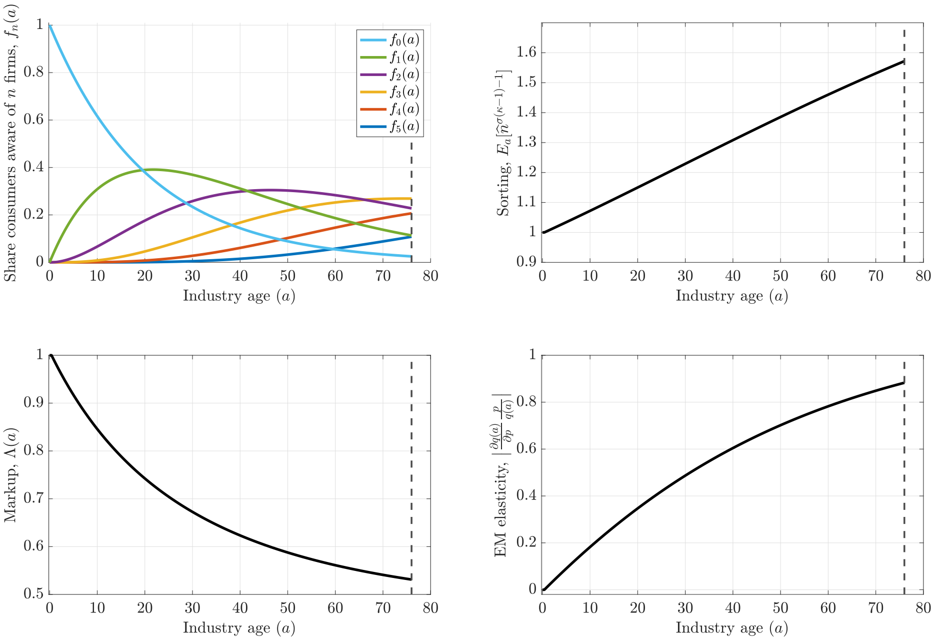

Equilibrium IV: Aggregation

▸ Closing the Model

- Stationary economy aggregates to a **Neoclassical Growth Model** with endogenous TFP:

1. **Aggregate markup:**

$$\boldsymbol{\Lambda} \equiv \left(\int_0^{+\infty} \varphi(a) \left(\Lambda(a) \right)^{-1} \mathrm{d}\Phi(a) \right)^{-1} \geq 1, \qquad \text{where } \varphi(a) \equiv \frac{p(a)y(a)}{\boldsymbol{Y}}$$

2. **Income shares**:

$$\frac{w\boldsymbol{L}}{\boldsymbol{Y}} = (1-\alpha)\boldsymbol{\Lambda}^{-1}; \qquad \frac{(r+\delta_K)\boldsymbol{K}}{\boldsymbol{Y}} = \alpha\boldsymbol{\Lambda}^{-1}; \qquad \frac{\boldsymbol{\Pi}}{\boldsymbol{Y}} = 1 - \boldsymbol{\Lambda}^{-1}.$$

3. **Aggregate output**:

$$\boldsymbol{Y} = \underbrace{\underbrace{z}_{\text{Physical TFP}} \underbrace{\boldsymbol{M}^{\frac{1}{\kappa-1}}}_{\text{Love-of-variety}} \underbrace{\boldsymbol{Q}}_{\text{Aggregate quality}} \underbrace{\boldsymbol{\Lambda}}_{\text{Markup wedge}}}_{\boldsymbol{Z} \,\equiv\, \text{Endogenous TFP}} \boldsymbol{K}^{\alpha} \boldsymbol{L}^{1-\alpha}, \quad \text{with } \boldsymbol{Q} \equiv \left[\int_0^{+\infty} \underbrace{\left(1 - f_0(a)\right)}_{\text{Awareness}} \underbrace{\mu(a)^{\sigma(\kappa-1)}}_{\text{Targeting}} \underbrace{q(a)}_{\text{Sorting}} \Lambda(a)^{1-\kappa} \, \mathrm{d}\Phi(a) \right]^{\frac{1}{\kappa-1}}$$

- Wedge $\boldsymbol{\Lambda}^{-1} \leq 1$ on income shares summarizes *all* misallocation generated from markup dispersion.

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Application:

The Rise of Targeted Advertising

Two Calibrations

- **Goal:** Quantify effects of ↑ targeting (rise in digital ADV in the 2000s) → 2 calibrations: ▸ Details
  1. **“Early” calibration (2005)** → *Low return* of ADV targeting.
  2. **“Late” calibration (2014)** → *High return* of ADV targeting (5 times higher, Farahat and Bailey (2012)).

Parameter		Value	Moment	Data	Model
A. “Early” calibration (2005)					
Product differentiation	σ	0.4183	Average markup (sales-weighted)	0.4674	0.4658
Category creation efficiency	z_M	0.1059	Mass of categories (M)	1.0000	1.0000
Contact rate cost	ν	0.0267	Advertising share of GDP	0.0220	0.0220
Targeting cost	η	0.2527	Return to targeting	0.0482	0.0482
B. “Late” calibration (2014)					
Product differentiation	σ	0.4099	Average markup (sales-weighted)	0.4850	0.4603
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Contact rate cost	ν	0.0229	Advertising share of GDP	0.0224	0.0224
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- Digital ADV rises → Both contacting (ν) and targeting (η) become cheaper, but targeting relatively more so:

$$\frac{\eta_{\text{early}}}{\nu_{\text{early}}} = \mathbf{9.5} \gg \mathbf{1.5} = \frac{\eta_{\text{late}}}{\nu_{\text{late}}}$$

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Implications of the Rise of Targeted Advertising

		2005	2014	% change
Contact rate	θ	1.924	1.853	–3.7%
Targeting rate	μ_0	1.230	2.088	+69.8%
Average targeting	$\int \mu(a)^{\sigma(\kappa-1)} d\Phi(a)$	0.023	0.101	+339.1%
Wage	w	2.087	2.205	+5.7%
Aggregate consumption	$\boldsymbol{C}$	2.977	3.123	+4.9%
Match quality	$\boldsymbol{Q}$	1.474	1.529	+3.7%
Aggregate markup	$\boldsymbol{\Lambda}$	1.466	1.460	–0.4%
Distortion-adjusted quality	$\boldsymbol{Q\Lambda}$	2.161	2.233	+3.3%
Output level	$\boldsymbol{Y}$	4.589	4.829	+5.2%
Aggregate TFP	$\boldsymbol{Z}$	2.161	2.233	+3.3%

- Since targeting is now relatively cheaper than contacting:
  - Targeting μ_0 goes up strongly $\rightarrow$ Firms get better at finding customers with higher taste (match quality $\uparrow$).
  - Contact rate θ decreases slightly $\rightarrow$ Firms find fewer new customers per unit of time (sorting $\downarrow$).
  - *In net...* Strong increase in welfare $\rightarrow$ Consumption $\uparrow$ by 4.9%, coming from...
    - ... higher aggregate quality ($\boldsymbol{Q}\uparrow$).
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▸ More – Effects within product category

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More – Effects within product category

Counterfactual Experiments I

- How did improvement in ADV technologies impact markups, product market dynamics and welfare?
- **Exercise:** Starting from 2014 economy ...
  - ... Both ADV cost parameters, ν (contacting) and η (targeting), are set back to their 2005 values.
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Results: If there had been no reduction in ADV costs $\rightarrow$ Less targeting ($\downarrow$ 40.9%) and faster contact ($\uparrow$ 5.2%).

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1. **Negative effects:**
   - ... aggregate consumer-firm match quality Q would have worsened.
2. **Positive effects:**
   - ... awareness would have accumulated faster $\rightarrow$ Stronger competition for customers $\rightarrow$ Markups $\downarrow$
   - ... markup distortions Λ would have been lower $\rightarrow$ Profit share lower, $(1 - \Lambda^{-1}) \downarrow$
   - ... GE effects:
     1. ... There would have been more product varieties ($M \uparrow$).
     2. ... Welfare (per-product consumption) would have been higher ($C/M \uparrow$).

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Counterfactual Experiments II

Full Table   Other Experiments

		Early (base)	Late (base)	Late (cf)	Change (wrt late base)
Contact rate	θ	1.924	1.853	1.949	+5.16%
Targeting rate	μ_0	1.230	2.088	1.236	-40.81%
Consumption share	C/Y	0.649	0.647	0.650	+0.56%
Advertising share	D/Y	0.022	0.022	0.021	-5.44%
Profit share	Π/Y	0.318	0.315	0.314	-0.46%
Mass of categories	M	1.000	1.000	1.183	+18.32%
Aggregate consumption	C	2.977	3.123	3.770	+20.72%
Normalized consumption	C/M	2.977	3.123	3.186	+2.03%
Match quality	Q	1.474	1.529	1.462	-4.40%
Aggregate markup	Λ	1.466	1.460	1.457	-0.24%
Distortion-adjusted quality	$Q\Lambda$	2.161	2.233	2.130	-4.60%
Output level	Y	4.589	4.829	5.798	+20.05%
Aggregate TFP	Z	2.161	2.233	2.521	+12.88%

Conclusion

- Study implications of targeted ADV for product market dynamics and macroeconomic aggregates.
- Theory:
  - Consumers are unaware of some products.
  - ADV affects: (i) speed at which new consumers are contacted; (ii) prob. of contacting high-valuation consumers.
- Application:
  - Rise in targeting driven by a decrease in both cost of targeting and cost of contacting.
  - Generates an increase in welfare (through better matches).
  - **Counterfactual:** Had rise in targeting not been accompanied by technological change...
    - ... match quality would have been lower.
    - ... still, welfare would have been higher, due to lower markup distortions.

Thank you!

Appendix

Appendix: Evolution of Awareness

Back

- In eq'm, it is sufficient to keep track of the size of awareness sets as a function of product category age.
  - Let $f_n(a)$ be the proportion of consumers aware of $n \in \{0, 1, \ldots, N\}$ firms at age $a > 0$.
  - We assume $\vec{f}(a) \equiv \left[f_0(a), f_1(a), \ldots, f_N(a)\right]^\top \in [0,1]^{N+1}$ evolves according to:

$$\frac{\partial \vec{f}(a)}{\partial a} = \vec{f}(a) \cdot \mathcal{Q}$$

with

$$\mathcal{Q} = \begin{bmatrix} -\theta & \theta & 0 & 0 & \ldots & 0 & 0 & 0 \\ 0 & -\frac{N-1}{N}\theta & \frac{N-1}{N}\theta & 0 & \ldots & 0 & 0 & 0 \\ 0 & 0 & -\frac{N-2}{N}\theta & \frac{N-2}{N}\theta & \ldots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & 0 & -\frac{1}{N}\theta & \frac{1}{N}\theta \\ 0 & 0 & 0 & 0 & \ldots & 0 & 0 & 0 \end{bmatrix}.$$

- *Intuitively:*
  - Each consumer has an intensity $\theta > 0$ (the *contact rate*) of becoming aware of a particular firm in the category.
  - When the consumer is aware of $n \leq N$ firms, the intensity with which she becomes aware of a new firm is $\frac{N-n}{N}\theta$.

Appendix: Firm Demand (1/2)

Back

Firm demand. In a symmetric equilibrium with $p(a) = p_{-i}$ and $\mu(a) = \mu_{-i}$, firm i's demand function is:

$$y_t(a) \;=\; \underbrace{(1 - f_0(a))}_{\text{Awareness}} \underbrace{\mu(a)^{\sigma(\kappa-1)}}_{\text{Targeting}} \underbrace{p(a)^{-\kappa}\frac{\Omega_t}{N}}_{\text{Downward-sloping demand}} \underbrace{\mathbb{E}_a\left[\widehat{n}^{\sigma(\kappa-1)}\right]}_{\text{Sorting} \equiv q(a)}$$

1. **Awareness:**
   - $f_n(a) \equiv$ Share of consumers aware of $n = 0, 1, \ldots, N$ firms at age a.
   - Thus, the more consumers are aware of the existence of product category m, the higher is demand (for all firms).
2. **Targeting:**
   - Targeting shifts demand, until network eventually becomes saturated ($f_N(a) \to 1$, so $s(a) \to 1$ and $\mu(a) \to 1$).
3. **Downward-sloping demand:**
   - *Intensive-margin* component $\rightarrow$ Current customers of firm demand more intensively if $p \downarrow$ and/or $\Omega \uparrow$.
4. **Sorting:**
   - *Extensive-margin* component $\rightarrow$ *Consumer sorting*, where $\widehat{n}$ denotes size of (non-empty) awareness set.
   - Larger awareness sets $\Rightarrow$ Consumers have more scope to sort toward better products. $\Rightarrow$ Sorting $\uparrow$

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$$y_t(a) = \underbrace{(1 - f_0(a))}_{\text{Awareness}} \underbrace{\mu(a)^{\sigma(\kappa-1)}}_{\text{Targeting}} \underbrace{p(a)^{-\kappa} \frac{\Omega_t}{N}}_{\text{Downward-sloping demand}} \underbrace{\mathbb{E}_a \left[\widehat{n}^{\sigma(\kappa-1)} \right]}_{\text{Sorting } \equiv q(a)}$$

1 **Awareness:**

- $f_n(a) \equiv$ Share of consumers aware of $n = 0, 1, \ldots, N$ firms at age a.
- Thus, the more consumers are aware of the existence of product category m, the higher is demand (for all firms).

2 **Targeting:**

- Targeting shifts demand, until network eventually becomes saturated ($f_N(a) \to 1$, so $s(a) \to 1$ and $\mu(a) \to 1$).

3 **Downward-sloping demand:**

- *Intensive-margin* component $\to$ Current customers of firm demand more intensively if $p \downarrow$ and/or $\Omega \uparrow$.

4 **Sorting:**

- *Extensive-margin* component $\to$ *Consumer sorting*, where $\widehat{n}$ denotes size of (non-empty) awareness set.
- Larger awareness sets $\Rightarrow$ Consumers have more scope to sort toward better products. $\Rightarrow$ Sorting $\uparrow$

Appendix: Firm Demand (2/2)

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- In an equilibrium with symmetric strategies, $\vec{p}_{-i} = \{p_{-i}, \ldots, p_{-i}\}$ and $\vec{\mu}_{-i} = \{\mu_{-i}, \ldots, \mu_{-i}\}$, demand is:

$$y(a,p) = (1 - f_0(a))\mu(a)^{\sigma(\kappa-1)} p^{-\kappa} \frac{\Omega_t}{N} \underbrace{\mathbb{E}_a \left[\widehat{n} \left(1 + (\widehat{n} - 1) \frac{\mu_{-i}}{\mu(a)} \left(\frac{p_{-i}}{p} \right)^{-\frac{1}{\sigma}} \right)^{\sigma(\kappa-1)-1} \right]}_{\text{Sorting component of demand}}$$

- Targeting $\mu(a) = \mu_0^{1-s(a)}$ affects demand in two ways:
  1. Shifts idiosyncratic demand conditional on purchasing, $\mu(a)^{\sigma(\kappa-1)-1}$.
  2. Shifts market power relative to competitors, $\dfrac{\mu_{-i}}{\mu(a)}$.
- In a symmetric equilibrium, $\mu(a) = \mu_{-i}$, only the first effect exists.

Appendix: Closing the Model (1/2)

Back

- Thanks to aggregation $\rightarrow$ Can solve for consumption-savings problem *as if* it came from representative HH.

$$\max_{\boldsymbol{C}_t, \boldsymbol{I}_t^K, \boldsymbol{I}_t^M} \int_0^{+\infty} e^{-\rho t} \frac{\boldsymbol{C}_t^{1-\gamma}}{1-\gamma} \mathrm{d}t \quad \text{s.t.} \quad \begin{cases} \dot{\boldsymbol{K}}_t = \boldsymbol{I}_t^K - \delta_K \boldsymbol{K}_t \\ \dot{\boldsymbol{A}}_t = \underbrace{r_t \boldsymbol{A}_t}_{\text{Financial income}} + \underbrace{w_t}_{\text{Labor income}} + \underbrace{(r_t + \delta_K) \boldsymbol{K}_t}_{\text{Returns from renting } K \text{ to firms}} - \underbrace{\left(\boldsymbol{C}_t + \boldsymbol{I}_t^K + \boldsymbol{I}_t^M \right)}_{\text{Consumption and investment expenditures}} + \underbrace{z_M \boldsymbol{I}_t^M \boldsymbol{V}_t^0}_{\text{Returns from category creation}} \end{cases}$$

- Household trades in firm shares:

$$\boldsymbol{A}_t = \boldsymbol{M}_t \int_0^{+\infty} V_t(a) \, \mathrm{d}\Phi_t(a), \quad \text{where } V_t(a) \equiv \underbrace{\int_t^{+\infty} e^{-\int_t^s (r_\tau + \delta_M) \mathrm{d}\tau} N \pi_s(a+s-t) \mathrm{d}s}_{\text{Value of a product category at age } a \geq 0}.$$

- Age-zero **advertising choices**:
  - When new product category is created ($a = 0$), blueprint owner chooses (θ, μ_0), common to all firms:

$$\boldsymbol{V}_t^0 \equiv \max_{\theta, \mu_0} \left\{ V_t(0) - N\left(\nu\theta^2 + \eta(\mu_0 - 1)^2 \right) \right\}$$

  - Optimal choices $\rightarrow$ $\theta_t^* = \dfrac{1}{2N\nu} \dfrac{\partial V_t(0)}{\partial \theta}$ and $\mu_{0,t}^* = 1 + \dfrac{1}{2N\eta} \dfrac{\partial V_t(0)}{\partial \mu_0}$.

Appendix: Closing the Model (2/2)

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- A few more equations to close the model:

1. Euler equation:

$$\frac{\dot{\boldsymbol{C}}_t}{\boldsymbol{C}_t} = \frac{r_t - \rho}{\gamma}$$

2. Resource constraint:

$$\boldsymbol{Y}_t = \boldsymbol{C}_t + \boldsymbol{I}_t^K + \boldsymbol{I}_t^M + z_M \boldsymbol{I}_t^M N \Big(\nu\theta^2 + \eta(\mu_0 - 1)^2 \Big)$$

3. Product category free entry condition:

$$z_M \boldsymbol{V}_t^0 \leq 1 \quad \text{with equality if, and only if, } \boldsymbol{I}_t^M > 0$$

4. Invariant distribution of product categories:

$$\frac{\mathrm{d}\Phi(a)}{\mathrm{d}a} = 1 - e^{-\delta_M a}$$

Appendix: Calibration

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- Parameters $(N, z, \rho, \kappa, \alpha, \gamma, \delta_K, \delta_M)$ are set externally.

Parameter		**Value**	**Source/Target**
Number of firms per product category	N	10	
Firm-level productivity	z	1	
Connection destruction rate	ζ	0	
Time discount rate	ρ	0.04	4% annual interest rate
Cross elasticity of substitution	κ	2	Oberfield and Raval (2021)
Capital share of non-profit income	α	0.33	Capital share of non-profit income
Coefficient of relative risk aversion	γ	2	Havranek et al. (2015)
Capital depreciation	δ_K	0.069	Celik et al. (2022) and U.S. NIPA tables
Product destruction rate	δ_M	0.09	Broda and Weinstein (2010)

- Parameters (σ, z_M, ν, η) are calibrated internally $\rightarrow$ 4 targets for each calibration ("early" and "late"):
  1. Mass of categories $\rightarrow$ Normalized to $\boldsymbol{M}_t = 1$ in both calibrations (pins down z_M).
  2. Average markup $\rightarrow$ From 46.7% (2005) to 48.5% (2014), using estimates from De Loecker et al. (2020).
  3. Advertising share of GDP $\rightarrow$ From 2.20% (2005) to 2.13% (2014), using data from Greenwood et al. (2021).
  4. Return to targeting:
     - Farahat and Bailey (2012) $\rightarrow$ Targeting $\uparrow$ click-through rate for brands by 79%.
     - Share of digital in total ADV rose from 6% (2005) to 30% (2014).
     - Adjusting for this, return to targeting $\rightarrow$ From 0.048 (2005) to 0.213 (2014) $\rightarrow$ A nearly 5-fold increase.

Appendix: Rise of Targeted Advertising (1/2)

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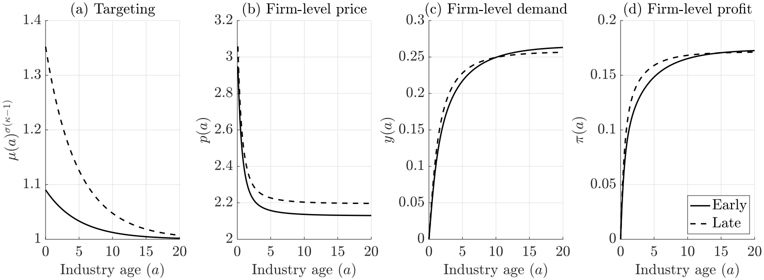

- Awareness spreads more slowly.
- Targeting is much higher, especially at early stages of the product category.
- Firms charge higher prices throughout.
- Demand and profits ↑ early.

- Components of demand (in logs):

$$\ln(y) = \ln(1 - f_0) + (\sigma(\kappa - 1) - 1)(1 - s)\ln(\mu_0) + \ln(\Omega/N) - \kappa \ln(p(a)) + \ln\left[\mathbb{E}_a(\hat{n}^{\sigma(\kappa-1)-1})\right]$$

where $s = \frac{1}{N}\sum_{n=1}^{N} n f_n(a)$ [saturation].

Appendix: Rise of Targeted Advertising (1/2)

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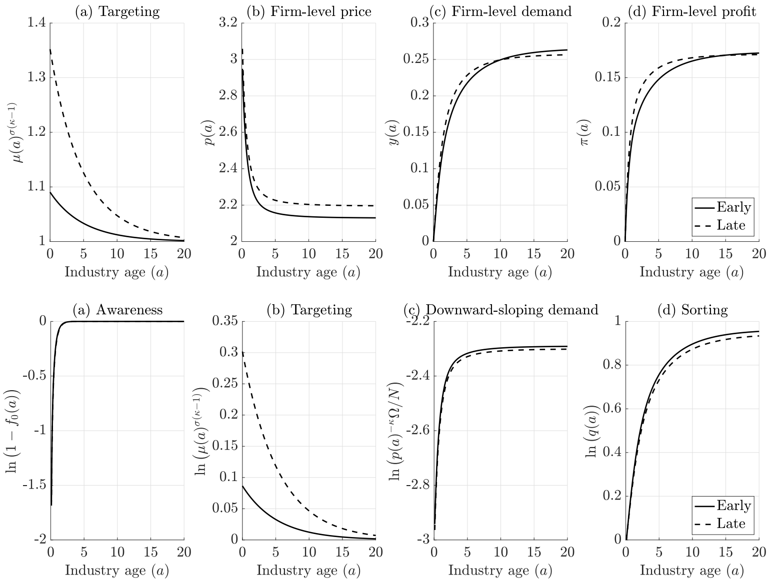

- Awareness spreads more slowly.
- Targeting is much higher, especially at early stages of the product category.
- Firms charge higher prices throughout.
- Demand and profits $\uparrow$ early.

- Components of demand (in logs):

$$\begin{aligned}\ln(y) = {} & \ln(1-f_0) \\ & + (\sigma(\kappa-1)-1)(1-s)\ln(\mu_0) \\ & + \ln(\Omega/N) - \kappa\ln(p(a)) \\ & + \ln\left[\mathbb{E}_a\left(\hat{n}^{\sigma(\kappa-1)-1}\right)\right]\end{aligned}$$

where $s = \frac{1}{N}\sum_{n=1}^{N} nf_n(a)$ [saturation].

Appendix: Rise of Targeted Advertising (2/2)

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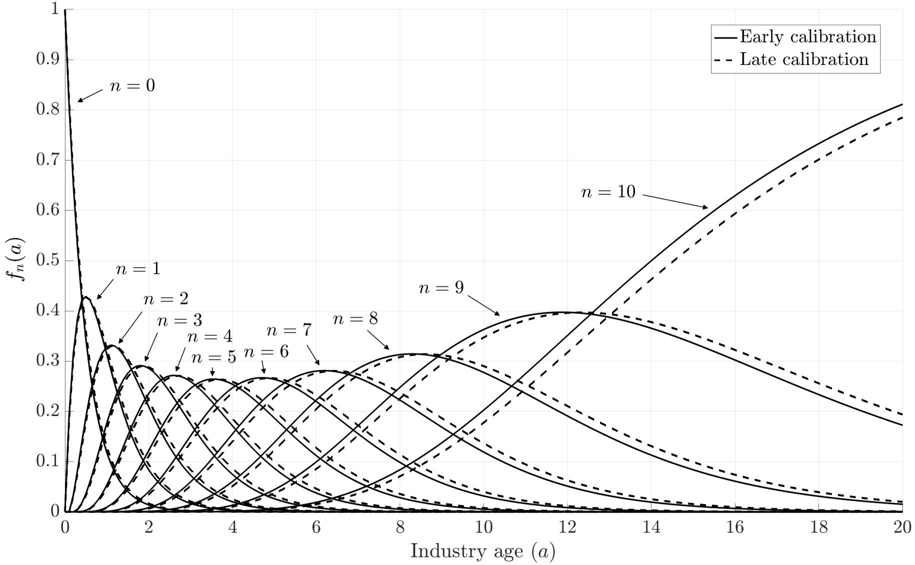

Appendix: Counterfactual Experiments (Full Table)

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		Early (base)	**Late** (base)	**Late** (cf)	**Change** (wrt late base)
A. Advertising and Markups					
Contact rate	θ	1.924	1.853	1.949	+5.16%
Targeting rate	μ_0	1.230	2.088	1.236	-40.81%
B. GDP Shares					
Consumption share	C/Y	0.649	0.647	0.650	+0.56%
Advertising share	D/Y	0.022	0.022	0.021	-5.44%
Category creation inv. share	I^M/Y	0.185	0.186	0.184	-1.44%
Capital investment share	I^K/Y	0.144	0.144	0.145	+0.21%
Profit share	Π/Y	0.318	0.315	0.314	-0.46%
C. Aggregates					
Wage	w	2.087	2.205	2.653	+20.31%
Mass of categories	M	1.000	1.000	1.183	+18.32%
Aggregate consumption	C	2.977	3.123	3.770	+20.72%
Normalized consumption	C/M	2.977	3.123	3.186	+2.03%
Match quality	Q	1.474	1.529	1.462	-4.40%
Aggregate markup	Λ	1.466	1.460	1.457	-0.24%
Distortion-adjusted quality	$Q\Lambda$	2.161	2.233	2.130	-4.60%
Output level	Y	4.589	4.829	5.798	+20.05%
Aggregate TFP	Z	2.161	2.233	2.521	+12.88%

Appendix: Other Counterfactual Experiments

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		(1) Early (base)	(2) Late (base)	(3) Late (ν_{2005}, η_{2005})	(4) Change wrt (2)	(5) Late (ν_{2005})	(6) Change wrt (2)	(7) Late (η_{2005})	(8) Change wrt (2)
A. Advertising and markups									
Contact rate	θ	1.924	1.853	1.949	+5.16%	1.748	-5.66%	2.066	+11.47%
Targeting rate	μ_0	1.230	2.088	1.236	-40.81%	2.118	+1.46%	1.227	-41.22%
B. Shares of GDP									
Consumption share	C/Y	0.649	0.647	0.650	+0.56%	0.647	+0.00%	0.650	+0.53%
Advertising share	D/Y	0.022	0.022	0.021	-5.44%	0.023	+3.97%	0.020	-8.84%
Category creation inv. share	I^M/Y	0.185	0.186	0.184	-1.44%	0.186	-0.42%	0.185	-1.00%
Capital investment share	I^K/Y	0.144	0.144	0.145	+0.21%	0.144	-0.09%	0.145	+0.29%
Profit share	Π/Y	0.318	0.315	0.314	-0.46%	0.316	+0.21%	0.313	-0.64%
C. Economic aggregates									
Wage	w	2.087	2.205	2.653	+20.31%	2.272	+3.04%	2.552	+15.74%
Mass of categories	M	1.000	1.000	1.183	+18.32%	1.027	+2.70%	1.143	+14.25%
Aggregate consumption	C	2.977	3.123	3.770	+20.72%	3.221	+3.14%	3.623	+16.02%
Normalized consumption	C/M	2.977	3.123	3.186	+2.03%	3.136	+0.42%	3.171	+1.55%
Match quality	Q	1.474	1.529	1.462	-4.40%	1.519	-0.67%	1.476	-3.51%
Distortion-adjusted quality	$Q\Lambda$	2.161	2.233	2.130	-4.60%	2.220	-0.58%	2.148	-3.79%
Output level	Y	4.589	4.829	5.798	+20.05%	4.981	+3.14%	5.574	+15.41%
Aggregate TFP	Z	2.161	2.233	2.521	+12.88%	2.280	+2.11%	2.455	+9.92%